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Uncertainty management in a macro life cycle assessment of a 2005–2025 European bioenergy policy

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ABSTRACT

This paper examines the uncertainty of a new method – the macro life cycle assessment – to analyze the environmental impacts of public policies. The environmental impacts of two 2005–2025 European energy policies (a business as usual policy and a bioenergy policy) were comparatively assessed and their uncertainty was computed. Following the inventory of each source of uncertainty, uncertainty management methods were sequentially applied to manage these sources whenever possible. Results show that the bioenergy policy causes lower environmental impacts in three of the four environmental damage categories (human health, climate change and natural resources), but more significantly in one (ecosystems). The risk of the business as usual policy causing lower environmental impacts is expected to be low. However, current knowledge makes it impossible to account for all sources of uncertainty or implement advanced uncertainty methods for all elements in the cause-effects chains involved in each European energy policy. Current uncertainty management methods are not adapted to the uncertainty of large models such as the macro life cycle assessment. Hence, while current results are promising, further work is required to improve uncertainty management in macro life cycle assessment.

Contents

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1. Introduction

With the rise of global environmental issues, international protocols are often required to provide solutions. For instance, the Montreal Protocol on substances that deplete the ozone layer was implemented in 1987 and the Kyoto Protocol to mitigate climate change came into force in 2005. When protocols define objectives like the reduction of halogenated hydrocarbon emissions (Montreal Protocol) or greenhouse gas emissions (Kyoto Protocol), different measures may be implemented to achieve these objectives. In the case of climate change mitigation, many environmental policies have been proposed to substitute fossil fuels with renewable sources of energy. Among them, the production of fuels from biomass for transport is quite popular since the use of so-called biofuels may double over the 2010–2030 period [1]. However, several studies have recently highlighted an unwanted indirect effect of biofuel policies: the competition with agriculture for land use may lead to significant GHG emissions from carbon stock, canceling the benefits of the oil-based fuel replacement with biofuels over the short term [2–4]. This highlights the necessity of assessing these environmental policies from a global perspective in order to forecast unwanted effects before they occur. Another point regarding these studies is the uncertainty on final results. The assumptions made in these studies and the models used are sources of significant uncertainty, making the final result highly uncertain.

Among the tools used to study environmental impacts, life cycle assessment (LCA), as defined by ISO standards (ISO 14040 and 14044), is a holistic method that makes it possible to compute the potential environmental impacts of a product or service based on several environmental impact categories. The impacts are related to resource consumption or pollutant emissions occurring at each life cycle stage of a product or service. Recently, a new LCA approach, the macro LCA (M-LCA) was developed to extend the LCA methodology adapted to the product or service assessment up to policy assessment [5]. The principle of M-LCA is to use the GTAP model [6], an economic general equilibrium model (GEM), to compute the economic consequences of the life cycles changes planned according to a policy and then use LCA methodology to convert these economic consequences into environmental impacts. In Dandres et al. [7], M-LCA was used to evaluate two European Union (EU) energy policies (a bioenergy policy and a business as usual energy policy) over the 2005–2025 period. As in studies conducted by Fargione et al. [2], Searching et al. [3] and US EPA [4], the uncertainty related to final results is expected to be significant, making the identification of the policy causing the less environmental impacts difficult. Indeed, uncertainty is known to be potentially high in economic GEM [8] and LCA [9–11]. The investigation of uncertainty in M-LCA is therefore justified. For this purpose, the results of the existing M-LCA case study [7] conducted to assess the environmental impacts of a EU bioenergy policy implemented in 2005–2025 has been used.

2. Method

The M-LCA method (summarized in Fig. 1) uses both the GTAP model and LCA methodology to assess environmental impacts due to significant changes occurring in one or several life cycles of one or a group of products or services. The process relies on the GTAP model to compute the economic consequences of a change occurring in one or several life cycles and the LCA methodology

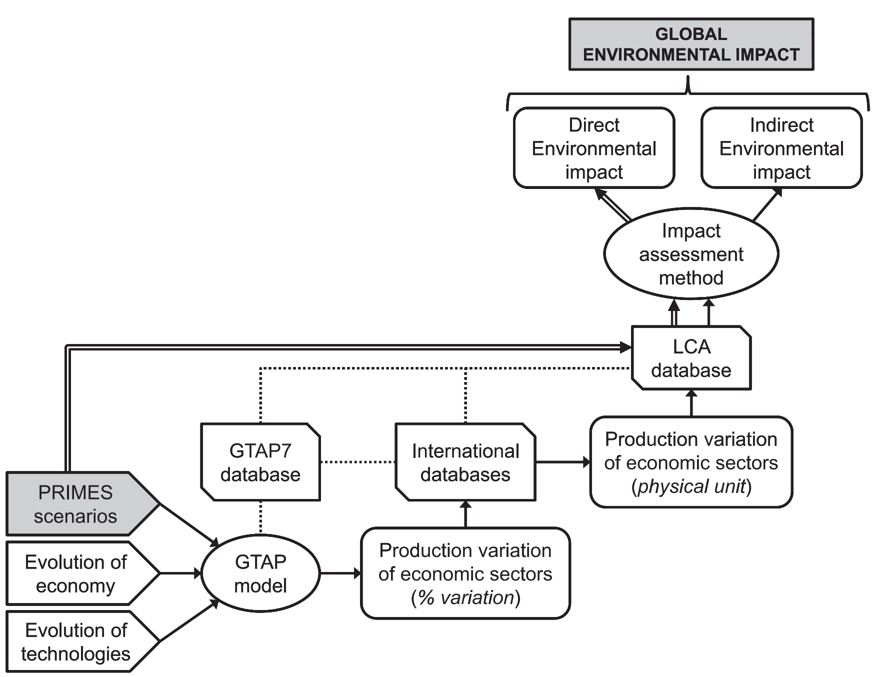

Fig. 1. Overview of the macro life cycle assessment (M-LCA) method. Legend: Two arrows go from the *PRIMES scenario* box: one arrow goes to the GTAP model in order to model the indirect economic consequences of the EU energy policies (and then the indirect environmental impact) while the other goes directly to the *LCA database* box in order to model the direct environmental impacts of the life cycle of the EU energy sector.

to calculate the potential environmental impacts caused by the variations in production of each economic sector modeled by GTAP (i.e. the economic consequences). The results of an M-LCA comparing the environmental impacts of two EU energy policies over 2005–2025 [5,7] is used in this paper to illustrate the method proposed to manage uncertainty.

The next paragraphs describe each step of the M-LCA and the method used in this paper to address the different sources of uncertainty.

2.1. PRIMES scenarios

The EU energy policies studied in Dandres et al. [7] were adapted from scenarios developed by Mantzos et al. [12] who used the PRIMES partial equilibrium economic model [13] to simulate the European energy sector. For the purpose of the uncertainty analysis presented here, PRIMES scenarios are considered to be fixed parameters (i.e. no uncertainty is attributed to these scenarios and therefore they are not included in the sensitivity or uncertainty analyses). The justification behind this is that the objective of this paper is to study the uncertainty affecting the comparison of two specific EU energy policies rather than to study the global uncertainty related to the future development of the EU energy sector. Thus the two EU energy policies are certain and can be considered as *what-if scenarios* as defined by Borjeson et al. [14]. These two scenarios are defined in Dandres et al. [7] and summarized here: one assumes a significant increase in the use of biomass to generate energy (the bioenergy scenario) and the other forecasts a business as usual development of the EU energy sector (the baseline scenario).

2.2. Economic evolution

Implementing expected economic changes in prospective GTAP studies is commonplace [15]. In Dandres et al. [7], these changes were taken into account for the following macroeconomic variables: population, labor force (skilled and unskilled), capital and gross domestic product. While the data used for the 2005–2010 period are based on real monitoring, the data used for the 2010–2025 period are prospective estimations (see Dandres et al. [7] for details). Consequently, the uncertainty of the 2010–2025 data is expected to be greater than the uncertainty of 2005–2010 data. However, no information on the uncertainty of any of these data was found. Therefore, sensitivity analyses were conducted to take the uncertainty of economic evolution into account (see Section 2.4.2 for details).

2.3. Technological evolution

Owing to the long temporal horizon of the study (two decades), technological innovation was taken into account on two levels: for the EU energy sector in the computation of direct environmental impacts and for the whole economy in the calculation of the indirect environmental impacts. Data collected to model the EU energy sector are quite detailed and provide information for each technology used to generate heat and electricity in Europe between 2005 and 2025. These data were used to modify the life cycle inventory in terms of the natural resource consumption and pollutant emissions of each EU energy technology. At the whole economy level, far more generic data are used to model the technological evolution of each economic sector of the GTAP model. The uncertainty of the latter data is greater than that for the EU energy sector level because:

- Detailed data for each of the 6441 regional economic sectors of the GTAP model were not found (57 economic sectors times 113 regions in GTAP7 database);
- Each GTAP economic sector includes many different technologies, and technological innovation was therefore modeled as an average of the technologies included in each economic sector;
- The technological innovation implemented in GTAP for a specific economic sector allows the model to reduce the amount of commodities needed by the sector. Consequently, the life cycle inventory of emitted and extracted substances was not modified to prevent a double counting of the reduction in natural resource consumption. However, the approach did not make it possible to model a reduction in the emissions specific to each technology.

2.4. GTAP model

The GTAP model [6] is an economic model that represents the global economy through 57 economic sectors and 113 regions. It models economic changes (via numerous economic variables) in response to a perturbation defined by the user. In Dandres et al. [7], the perturbation impacts the EU heat and electricity sectors and macroeconomic and technological variables. The GTAP results used to compute the indirect environmental impacts are the production variations of each economic sector in each region of the world (with the exception of the EU energy sector which is planned in the EU policies and used as input in the GTAP model).

2.4.1. Sources of uncertainty

There are three types of uncertainty in the GTAP results:

1. Mathematical uncertainty due to the approximations made by the GTAP solver (GEMPACK) to solve the GTAP system of non-linear equations (thousands of equations);
2. Model uncertainty due to the use of assumptions and equations that do not perfectly reflect the reality of economic and non-economic phenomena; and
3. Uncertainty of the data used by the model to run simulations that is propagated to the GTAP results (including uncertainty in the variables modified by the user, also referred to as shocked variables).

While mathematical uncertainty is monitored and controlled in GTAP model (GEMPACK monitors solutions convergence comparing solutions computed with different methods and rejects solutions when they are too different since they are interpreted to have a too high mathematical uncertainty, refer to Harrison and Pearson [16] for more details), model and data uncertainty remain unknown and especially hard to assess due to:

- The difficulty in validating the model with historical data. Indeed, model validation with historical data is difficult to achieve because it would require information on a period in which non-economic events (natural disasters, embargos, economic policies, wars, etc.) did not influence the economy as well as data on all exogenous variables that changed during the considered period [6]; and
- The high quantity of data (thousands items) that are potentially uncertain with an unknown uncertainty that is propagated to the final results of the model.

2.4.2. Uncertainty management in GTAP

The propagation of data uncertainty can be evaluated using at least two approaches. The first relies on the functionality directly built into GTAP that runs sensitivity analyses based on the

Gaussian quadrature statistical approach [17,18]. The second consists in a scenario-based approach.

The uncertainty functionality built directly into GTAP provides a mean and standard deviation for each GTAP result. To proceed, the user must specify the type of the distribution probability and the range of values for each variable to be explored by GTAP in the sensitivity analysis. A drawback of the approach is the time required to run sensitivity analyses involving multiple uncertain variables, which can be very long, especially if variables are studied independently (one at a time). Concretely, the model must be run XN times, where X is the number of values taken by each variable and N is the number of variable included in the sensitivity analysis (also, N becomes high when all sectors and regions are involved in a variable). The temporal aspect becomes especially critical when the GTAP model is run in recursive mode, as in Dandres et al. [7]. In this particular case, several simulations are run to dynamically cover the temporal horizon, so, ultimately, the sensitivity analysis would require the model to be run XNM times, where M is the number of recursive simulations ($M=8$ in Dandres et al. [7]). Moreover, for technical reasons, internal variables and shocked variables cannot be analyzed at the same time, meaning that separate sensitivity analyses are required to account for the uncertainty of all variables and shocked variables. Finally, the only two distributions (linear and triangular) currently available for GTAP sensitivity analyses to characterize variable uncertainty may be too restrictive to reflect the real uncertainty of parameters [19]. Because of these multiple obstacles, the Gaussian quadrature statistical approach was rejected and the scenario-based approach was chosen.

The scenario-based approach has already been used by several authors [20–23] and consists in developing scenarios based on possible values for the uncertain variables and then running model simulations for each developed scenario. The main advantage of this approach is that it is more easily applied than the statistical approach described earlier when few computational and programming resources are available. Indeed, both computational resources and programming skills can affect the time required to conduct sensitivity analyses in GTAP and other GEM. While computational resources affect the time needed to run the GEM simulations, programming skills may decrease the time required to prepare the files used to run each simulation. However, until computational and programming resources are available simultaneously, the time required to conduct sensitivity analyses will not be significantly reduced. Additionally, due to the high number of variables in GEM, not all variables can be included in the scenario-based analysis in order to set up and run the required simulations within a reasonable time. A disadvantage of the scenario-based approach is that uncertainty information provided on the model results is less complete than those generated by a statistical approach such as a Monte-Carlo analysis [24]. In particular, the scenario approach does not yield probability distributions for model results. Instead, it provides worst and best cases based on values attributed to certain variables.

Table 1
Description of the assumptions made in each scenario and letters used to name each scenario.

Scenario letter	Variable group		
	Armington	Economy	Technology
A	–	–	–
B	–	–	0
C	–	–	+
D	0	–	–
E	0	–	0
F	0	–	+
G	+	–	–
H	+	–	0
I	+	–	+
J	–	0	–
K	–	0	0
L	–	0	+
M	0	0	–
N	0	0	0
O	0	0	+
P	+	0	–
Q	+	0	0
R	+	0	+
S	–	+	–
T	–	+	0
U	–	+	+
V	0	+	–
W	0	+	0
X	0	+	+
Y	+	+	–
Z	+	+	0
Π	+	+	+
Ω	0	0	0

2.4.3. *Uncertainty management in the case study*

In this study, the following GTAP variables were studied for uncertainty: macroeconomic variables, technological variables and Armington elasticities.

Macroeconomic variables were included in the uncertainty analysis because Dandres et al. [7] observed that they were a major influence on the results of GTAP simulations. Technological variables have smaller impacts on the GTAP simulations, but their uncertainty is expected to be significant. For this reason, they were also included in the uncertainty analysis. Armington elasticities are used by GTAP to handle competition between domestic and foreign products and are known to be very sensitive parameters in GTAP studies [25–28]. Therefore Armington elasticities were also included in the uncertainty analysis.

Three sets of values were considered for each variable: the first set was obtained by increasing the original values by 50%, the second set was obtained by decreasing them by 50% and the third set was composed of the original values.

Given the setting of the GTAP simulations (13 regions and 20 commodities) in Dandres et al. [7], there are 65 macroeconomic variables, 260 technological variables and 26 Armington elasticities for a total of 351 variables. Therefore, it was not possible to vary each variable independently of the others due to the high number of GTAP simulations that would be required (8 recursive simulations times 3^{351} combinations). Instead, groups of similar variables were varied. Three groups were formed: a macroeconomic group, a technological group and an Armington group. Then, all the variables of each group were varied together, independently of the variables of the other groups, leading to the creation of 27 uncertainty scenarios (3 groups of variables and 3 values for each group of variables), which were run recursively in 216 GTAP simulations (27 scenarios times 8 recursive simulations per scenario). The 27 scenarios and the letters used to refer to it are identified in Table 1. In this Table, "-" symbol means the original values are decreased by 50%; 0 means the original values are used without change; "+" symbol means the original values are increased by 50%.

While the uncertainty scenarios cover several cases, it is difficult to attribute a probability of occurrence for each of them. Indeed, such probabilities could be computed based on the probability distributions of the macroeconomic, technological and Armington variables, but such data are currently unavailable due to the impossibility of comparing the forecasts with the real future values of the variables. The probability of each case might also be assessed with a panel of experts but it would require

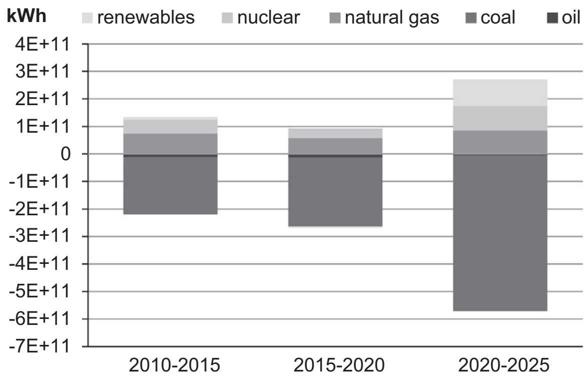

Fig. 2. Differences between the baseline and renewable North American energy scenarios, adapted from International Energy Agency [29].

significant resources and the results would still remain uncertain. For these reasons, a simpler approach was followed. Considering each situation is defined by a symmetrical change (± 50%) in the macroeconomic and technological variables, it was assumed each case has the same probability of occurrence. The limit of this approach is raised in the discussion.

Considering that the evolution of the macroeconomic and technological backgrounds may significantly impact the results of an M-LCA and that North America is a major energy consumer, a 28th scenario (Ω in Table 1) was developed based on the implementation of a North American renewable electricity policy occurring at the same time as in the EU in order to study whether a North American electricity policy would create economic interactions with the EU energy policy. As in Dandres et al. [7], two prospective energy scenarios were designed for North America. Both of these scenarios are adapted from the World Energy Outlook 2009 [29]: the first represents a business as usual development of the North American energy sector while the second forecasts a development of renewable electricity and an increase in energy efficiency. Fig. 2 illustrates the difference in electricity sources between the North American energy scenarios. In order to maximize the possible interaction between wood biomass supplies for the EU and North America, it was assumed that all renewable energy development in North America would be achieved with wood biomass. Though unrealistic, the situation is appropriate for the purpose of the sensitivity analysis conducted as part of this project.

The GTAP simulations were conducted by integrating the changes in the business as usual scenario into the baseline scenario, while the changes in the renewable scenario were added to the bioenergy scenario. The ecoinvent database used to list the life cycle emissions and extractions of substances was also modified in order to reflect the changes in the North American electricity sector in each scenario. Then, the direct environmental impacts of North American electricity generation were computed and added to the EU direct environmental impacts for each five-year period in 2005–2025.

2.5. International databases

The GTAP results used in M-LCA are expressed as a percent variation in the regional production of each economic sector. In order to compute the environmental impacts based on the production variation of each economic sector in each region, several databases must be synchronized to establish:

- The production of each regional economic sector for the GTAP7 reference year;
- The natural resource consumption and pollutant emissions of each regional economic sector.

Table 2
Methods to manage uncertainty in life cycle assessment.

Method	References
Sensitivity analysis	Cellura et al. [38] and Steen [35]
Monte-Carlo analysis	Huijbregts [39]
Bayesian Monte-Carlo analysis	Lo and Ma [11]
Boundaries analysis	Johnson and Willis [40]
Multivariate regression analysis	Wang and Li [41]
Combined approaches	Maurice et al. [42] and May et al. [43]

Data were therefore collected from several international databases [30–33] linked to the GTAP7 and ecoinvent LCA databases. Two main sources of uncertainty were identified in the process:

1. The uncertainty of the data collected from international databases;
2. The uncertainty of the linkages between the GTAP7, international and LCA databases (dot line in Fig. 1).

Unfortunately, the uncertainty of the data is not documented in the international database websites and is therefore unknown. Only the Food and Agriculture Organization of the United Nations provides a list of potential sources of uncertainty for its data [34].

Two issues generate uncertainty with regard to the links between databases:

1. Each database uses different nomenclatures to name its data or different aggregation to compute data. Therefore, it is never certain if a given name refers exactly to the same reality from one database to the next. This is especially true when names are not exactly the same (e.g. *Molybdenum concentrates, roasted* and *Molybdenum, at regional storage*) or quite imprecise (e.g. *cereals*).
2. Data from different databases are not always equivalent, since some data may be available in a given database but not in another. In such situations, proxies are sometimes available and may be used to fill data gaps, but it is not clear how the uncertainty of the proxy affects the uncertainty of the final results in M-LCA. More specifically, it is unclear whether it is best to use a quite uncertain proxy or omit it and assume zero for the missing data.

The higher number of data used also constitutes an obstacles when managing uncertainty in M-LCA: GTAP7 has 57 aggregated economic sectors linked to some 5000 economic activities in international databases and 1000 industrial processes in the LCA database (including 500 separate industrial processes, since a specific industrial process may be used as a proxy for several economic activities). Therefore, it is impossible to manually assess the uncertainty of each data (especially when linking databases) and then implement the data in an uncertainty management method. There is indeed a need to develop a method to manage such uncertainty. Additionally, data from international databases should be completed with uncertainty information that could be easily used in the uncertainty analysis.

For all these reasons and due to a lack of resources, the uncertainty related to the use of international databases was not included in the current uncertainty analysis.

2.5.1. Uncertainty in LCA

Uncertainty in LCA is widely documented:

- Steen [35] and Huijbregts [36] identified the sources of uncertainty in LCA;

- Weidema & Wesnaes [37] developed a pedigree matrix characterizing the quality of the data used in the life cycle inventory phase.

Various approaches can be applied to manage uncertainty in LCA and are listed in Table 2.

Among these methods, Monte-Carlo analysis is the most commonly used and was therefore chosen to manage LCA uncertainty in M-LCA [44–54]. A Monte-Carlo analysis consists in attributing a probability distribution of possible values to each uncertain parameter and then computing the LCA results using a random value for each parameter based on its probability distribution [24]. The calculation is reproduced a high number of times in order to obtain a probability distribution for the LCA results.

2.5.2. *Uncertainty of global environmental impacts*

In Dandres et al. [7], the inventory of the natural resource consumption and pollutant emissions of each industrial activity is based on the ecoinvent (version 2.0) database, which was slightly modified to reflect regional diversity in electricity generation and include additional processes in the food economic sector (the structure of the database was also modified to prevent double counting in the environmental assessment but it is not expected to affect uncertainty of the results, see Dandres et al. [5] for more details). SimaPro (version 7.3.2) LCA software was used to manage ecoinvent data and, though it can run Monte-Carlo simulations, for technical reasons, the Monte-Carlo analysis had to be split into two phases using both SimaPro and Microsoft Excel with the Crystal Ball plug-in (version 11). The first phase of the Monte-Carlo simulations was conducted with SimaPro (5000 iterations) to manage uncertainty in the environmental impacts of each process in the ecoinvent database used to model the processes of the GTAP7 database (some 500 different processes). These Monte-Carlo simulations were calibrated using the mean, standard deviations and probability of the ecoinvent database. In this Monte-Carlo analysis, the uncertainty was computed for unitary units (e.g. 1 metric ton, 1 m^3, etc.) and provided the probability distribution for each process and each damage category (human health, ecosystem, climate change and natural resources). Then, the standard deviation of each probability distribution was increased in order to take the uncertainty of ecoinvent data used in the wrong context into account. Indeed, the ecoinvent database, which is designed for European industries and for year 2000, is used in M-LCA to model industrial activities in other regions of the world between 2005 and 2025. Since the pedigree matrix of Weidema & Wesnaes [37] is implemented in ecoinvent for most processes and may be modified with SimaPro, it was possible to monitor the variations in standard deviations of ecoinvent processes when the quality of the data is changed from best values up to worst values. It was found that a 2.5 factor was the biggest variation in standard deviation. This factor was applied to all standard deviations obtained in the first phase. The factor probably overestimated the uncertainty of each industrial process because the 2.5 factor corresponds to the maximum gap between the worst and best data quality, while each process used in M-LCA may not have worst quality data. However, it would have been too time consuming to manually specify the standard deviation of each ecoinvent processes used in M-LCA (around 1000 processes).

Then, the second phase of the Monte-Carlo analysis using the results of the previous Monte-Carlo simulations and the variations in the production of each regional economic sector computed by GTAP for each energy policy was carried out in Microsoft Excel with the Crystal Ball plug-in (1000 iterations) to compute the probability distribution of the difference in environmental impacts between the baseline and bioenergy scenarios for each of the 28 uncertainty scenarios.

3. Results

The impact differences between the bioenergy and baseline scenarios for each environmental damage category in each uncertainty scenario are presented in Fig. 3 (each scenario is represented by a different letter as identified in Table 1). The differences in the impacts are computed by removing baseline scenario impacts from the bioenergy scenario. Thus, a positive value means that the bioenergy

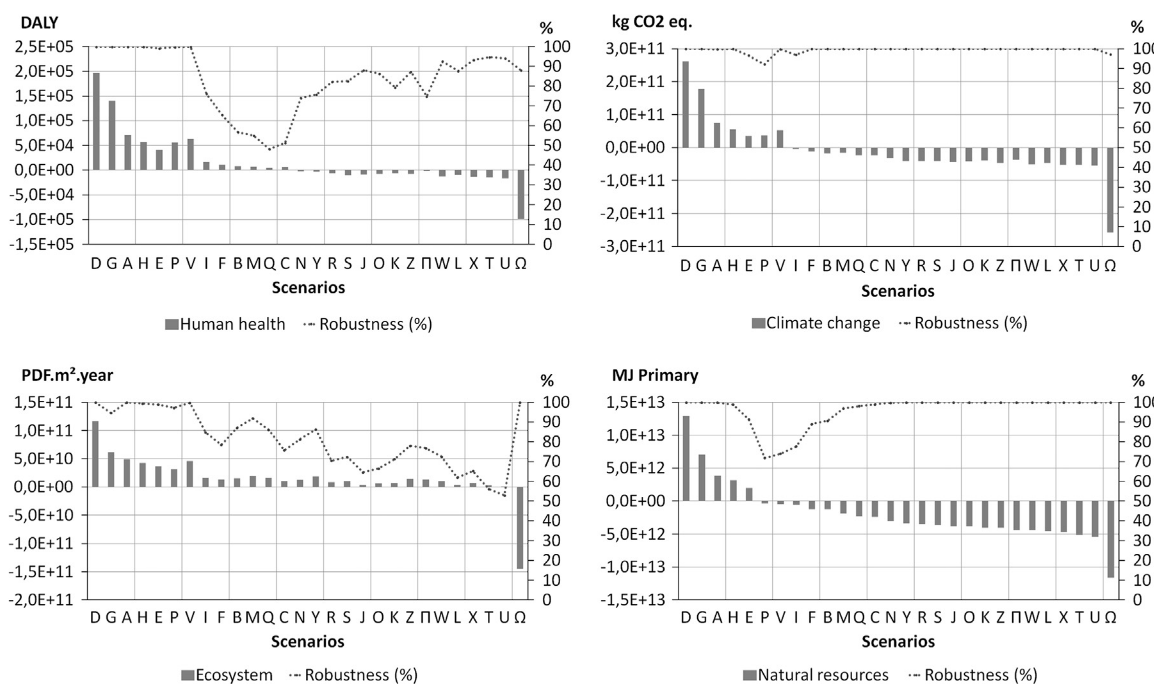

Fig. 3. Comparison of EU energy policy environmental impacts by damage category and the percentage of cases (based on the results of the Monte-Carlo simulations) that the direction of the comparison computed is valid.

scenario causes more environmental impacts than the baseline scenario, while a negative value means that it causes lower impacts. Fig. 3 also provides the percentage of chance (based on the results of the Monte-Carlo simulations) that the direction of the comparison is valid. For instance, in scenario I, the chances that the bioenergy scenario causes more impacts than the baseline scenario are 77% for the human health category and 85% for the ecosystems category, while the chances that the baseline scenario causes more impacts on climate change and natural resources are 97 and 78%.

It was found in Dandres et al. [7] that the bioenergy scenario causes lower impacts on human health, climate and natural resources than the baseline scenario but more impacts on ecosystems. These results are reproduced in the "N" scenario in Fig. 3 which is referred as the "reference scenario" later in the text. The uncertainty analysis conducted here completes the results obtained previously by Dandres et al. [7] regarding the comparison of the two EU energy policies.

The uncertainty analysis highlights several facts described below.

- In terms of sensitivity, the difference in impacts between EU energy policies does not differ from the reference scenario in most of the uncertainty scenarios. The impacts of the bioenergy scenario are significantly higher than those of the baseline scenario only in seven cases (D, G, A, H, E, P and V), which are characterized by low economic growth and or low technological development.
- Each environmental indicator is affected differently by the variations in the uncertain variables. While, in all cases, the bioenergy scenario causes more ecosystem damages than the baseline scenario, it causes more impacts on human health, climate change and natural resources in respectively thirteen, seven and five scenarios, of all 27. Thus, the environmental comparison of the EU energy policies made in Dandres et al. [7] is greatly affected for human health, slightly affected for climate change and natural resources and unaffected for ecosystems.
- Macroeconomic variables are more sensitive than technological and Armington variables, which are almost equally sensitive. Indeed, Table 3 shows that a weak economic growth situation leads to reversed results in the EU energy policies comparison in 19 scenarios (nine for human health, five for climate change and five for natural resources) of 25 scenarios (thirteen for human health, seven for climate change and five for natural resources), while this happens in respectively 14 and 12 scenarios for low technological development (six for human health, five for climate change and three for natural resources) and low Armington elasticities (six for human health, five for climate change and one for natural resources; all corresponding to situations in which domestic commodities are hardly substituted by imported commodities). Additionally, most of the time, significant economic growth or technological development leads to similar results in the comparison of the EU energy policies found in the reference scenario.
- The uncertainty in the impact difference between the energy policies differs from one damage category to the next. While there is less uncertainty in the climate change and natural resource categories (averages of 99.4 and 95.8% of the cases), there is more uncertainty in the human health and ecosystems categories (averages of 83.1 and 80.4% of the cases), including low values such as 50% of the cases for scenarios Q and C.
- The higher the absolute value of the difference in impacts between EU policies, the lesser the uncertainty in the policy comparison result. Thus, the low values of some of the percentages of cases observed in scenarios Q and C correspond to a situation in which the environmental differences between energy scenarios are among the smallest impact differences between the 28 uncertainty scenarios. In other words, it means both EU policies lead almost to the same impacts for scenarios Q and C.
- The 28th scenario involving simultaneous energy policies in the EU and North America presents lesser environmental impacts in the bioenergy scenario for all categories in almost all cases (average of 96.31% of the cases). This result is explained by the significant reductions in coal extraction in North America and other regions such as in South Africa, the Russian Federation and Australia, which are major coal producers, while it was observed that only South Africa significantly reduces its coal extraction when a bioenergy policy is implemented only in the EU (reference scenario N). This result confirms that the coal sector is a key factor in this environmental study. Therefore, combining a coal partial equilibrium model and the GTAP model in order to more precisely model the coal sector would certainly improve the results of this M-LCA.

Table 3
Number of scenarios in which an opposite result to the reference scenario N is observed, expressed by damage categories and variation types of uncertain variables.

	Human health	Ecosystem	Climate change	Natural resources
Technological growth				
Low	6	0	5	3
Average	4	0	2	2
High	3	0	0	0
Economic growth				
Low	9	0	5	5
Average	3	0	1	0
High	1	0	1	0
Armington elasticities				
Low	6	0	5	1
Average	4	0	2	2
High	3	0	0	2
Total	**13**	**0**	**7**	**5**

Legend: numbers represent the number of cases where an opposite result to the result of the reference scenario N is observed. For instance: in 13 of the 27 scenarios, it is observed in Fig. 3 that the bioenergy scenario is expected to cause more impact on human health than the baseline scenario. At the opposite, it was found in the N reference scenario that the bioenergy scenario would cause less impact on human health than the baseline scenario. Then, the 13 scenarios can be described according to the values taken by the group of economic, technological and Armington variables. Thus, it can be seen that six of the 13 scenarios have a low technological growth (values of technological variables decreased by 50% in comparison with the N reference scenario) while four occur under a regular technological growth (technological variables take the same values than in the N reference scenario) and three scenarios have a high technological growth (values of technological variables increased by 50% in comparison with the N reference scenario).

4. Discussion

If each uncertainty scenario has the same chance to occur in the future, then the bioenergy scenario causes lower impacts than the baseline scenario in 52% of the cases for human health, 0% for ecosystems, 74% for climate change and 81% for natural resources. Thus, if the four damage categories are considered at the same time, in 77% of cases, the results of the comparison of the EU energy policies made in Dandres et al. [7] remain unchanged when uncertainty in the GTAP variables and ecoinvent data is taken into account. However, these percentages are valid only if the uncertainty scenarios have the same probability of occurrence. Nevertheless, the results show that these percentages would be significantly affected only if the probability of the cases with low economic growth and/or technological development would be

higher than the probability of the other cases. While these factors may remain low on a short period it is not expected they remain low on the long term. Thus, the risk these percentages are significantly wrong is expected to be low.

Globally, the results show that, except for the human health indicator, the M-LCA method is relatively unaffected by uncertainty. However, not all uncertainty sources were taken into account. More specifically, uncertainties in the GTAP model (excluding uncertainty on Armington elasticities and shocked variables), data from international databases, database links and the environmental impact assessment method are not considered. It must also be noted that the Monte-Carlo simulation probably overestimated the uncertainty of the life cycle inventory for two reasons: all standard deviations were increased by a factor of 2.5 (as mentioned before) and no correlations between processes were made in the Monte-Carlo calculation. While, in reality, some uncertain data for certain processes would be the same, running the Monte-Carlo simulation separately for each process prevents the use of the same random numbers when it would have been required to fit with this reality. Thus, independent Monte-Carlo simulations may exaggerate the uncertainty of the results.

Considering all the aspects of the M-LCA, some developments were determined to enhance the method.

4.1. Additional data to fill data gaps

More LCA data are needed to reduce the data gap in database links and enhance the modeling of certain GTAP economic sectors:

- The entire tertiary sector (communications, financial services, insurance, business services, recreational services, public administration, defense, education, health, and housing);
- Certain manufactured products in the secondary sector (machinery/equipment, including transport and electronic equipment, chemical products, textiles and apparel); and
- Certain activities in the primary sector (food transformation and mineral extraction/transformation).

More data from international databases are required to improve database links and model these regional activities: transport (annual totals of mass transported and distance traveled for each mode of transport in each country), construction (annual new constructions by type and country) and heat generation (sources and annual amounts of heat generated by country). Also, additional LCA data are required to take the regional variability of industrial processes into account (ecoinvent is based on European data but is still used M-LCA to model industries in other regions despite possible technological differences).

4.2. Additional information about uncertainty to enhance the uncertainty analysis

This is especially true for data collected from international databases but also for models used to compute environmental impacts whose uncertainty is not taken into account in LCA Monte-Carlo simulations [55].

4.3. An assessment of GTAP model uncertainty

A comparison with historical data (or another approach if difficulties are too important) must be carried out in order to assess the uncertainty of GTAP results. This assessment should ideally make a distinction between the contributions of model and data uncertainty.

4.4. A new integrated method to manage uncertainty in large models

None of the techniques for variables sensitivity analysis reviews [56] or the uncertainty management methods developed especially for large models [57–59] seem adapted to M-LCA due to the high number of variables and equations. Two issues must be resolved in order to implement an acceptable uncertainty management method for M-LCA. First, the number of simulation iterations must be as low as possible to minimize computing time. Monte-Carlo simulations therefore do not constitute an adequate approach to handle uncertainty in large models, the exception being:

1. The availability of significant computational resources such as in Elliot et al. [60], which achieved a 30 000 CPU-hours Monte-Carlo simulation involving 2000 CPU.
2. The achievement of new methodological developments allowing a significant decrease in required iterations. Maybe this development could be attained with latin hypercube [61] and/or active learning [62] sampling.

A suitable approach for M-LCA could be based on aforementioned methods or use either the Gaussian quadrature approach (already implemented in GTAP) or the extended Fourier amplitude sensitivity testing, which is perceived as the most promising approach by Ravalico et al. [63] to conduct sensitivity analysis in environmental models used in decision-making. The second issue is uncertainty source management in an integrated approach. In the uncertainty analysis, a lot of time was spent preparing the files needed for each simulation, extracting and managing the intermediate data and compiling the results of the uncertainty analysis. Such operations could certainly be fully and efficiently automated with the use of a computer program that could handle the softwares used in M-LCA and manage all intermediate tasks.

4.5. Further knowledge of the uncertainty related to the future

Because M-LCA is a method to study the future consequences of decisions, it uses forecasts and makes assumptions about the future. It has been shown that macroeconomic variables play an important role in M-LCA simulations, so the uncertainty related to the future must be implemented in uncertainty management. However, the future is uncertain by definition, and several prospective scenarios are often used to manage uncertainty due to the future in LCA studies and economic modeling [14,22,55,64–72]. Ideally, the probability of occurrence of each prospective scenario should be assessed and implemented in the uncertainty approach. However, the uncertainty related to the future may remain unknown despite effort to assess it. Another type of approach may therefore be necessary to identify the best solution in the worst situation as outlined in Hites [73] rather than compute the uncertainty of the results.

5. Conclusion

In this paper, the issue of uncertainty management in large models is reviewed and discussed in the context of macro life cycle assessment (M-LCA) developed in Dandres et al. [5,7]. In the case study, the M-LCA results were shown to be relatively robust under the uncertainty conditions. The comparison of the two European Union (EU) energy policies showed that the EU bioenergy policy causes less environmental impacts in 77% of cases than the business as usual policy (percentage based on the average of all environmental indicators and an equal probability of occurrence of each uncertainty scenario). However, it is important to note that not all sources of uncertainty were taken into account when generating this result. A review of

uncertainty sources in M-LCA highlights the need for additional data, data of higher quality and better uncertainty management with regard to the computable general equilibrium model, impact assessment methods in life cycle analysis and prospective studies. Also, it appears that no method is currently able to manage uncertainty in large models without involving significant computational resources. Therefore, there is a need to develop an integrated approach that would manage the various sources of uncertainty when sequentially combining models.

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